# CZ1016 Test Notes

## Data Science Pipeline

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|---|---|
| **Practical Motivation**<br>- Can you relate the problem for Data | **Sample Collection**<br>- How to effectively sample real data |
| **Problem Formulation**<br>- How to construct a data science problem | **Data Preparation**<br>- How do I prepare raw data for analysis?<br>- Data Cleaning |
| **Statistical Description**<br>- How do I summarise/describe the data | **Exploratory Analysis**<br>- EDA<br>- Basic insights from the data |
| **Pattern Recognition**<br>- Can I find insights and patterns | **Analytic Visualization**<br>- How do I represent the data for reading |
| **Machine Learning**<br>- How to learn from the data | **Algorithmic Optimization**<br>- How to learn optimally from the data |
| **Statistical Inference**<br>- How to confidently infer from the data | **Information Presentation**<br>- How to communicate Data Analysis |
| **Intelligent Decision**<br>- How to solve a real-life problem by data<br>- Optimize the outcomes | **Ethical Considerations**<br>- How to responsibly work in Data Science |

## Preparing Data

- **Feature Scaling:** Normalize the data if it is too skewed and scale them accordingly before building the model
- **Boxplot:** Boxplot is useful as it gives a statistical summary of the data (Quartile ranges, Outliers etc). 5-point statistic that breaks open the data in equal proportion (25%)
- **Pair plot:** Useful to express bivariate relationship when there are multiple features
- **Histogram:** Counts data in intervals, shows you the frequency. (Mean and Variance associated with it and KDE)

## Analysing the Curve

- Normal Distribution: Mode = Mean = Median
- Negative Skew / Left Skew: Tail is longer to the left. Mean < Median < Mode
- Positive Skew / Right Skew: Tail is longer to the right. Mode < Median < Mean

## Linear Regression

- Find the best fit line to the data points
- y = β0 +β1x+ε is a general formula. (β0 is the intercept, β1-n represents the coefficients of each feature, ε/J represents the cost function)
- J(a, b) is the cost function where a , b represent the parameters of the coefficients and intercepts. Gradient descent is performed to try and minimize the cost function.
- Mean Squared Error:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

**Drawbacks of Linear Regression**

- Very sensitive to outliers in the datapoints
- Assumes Linearity relationship between the points

**Measure of accuracy of model**

**R-Squared (Explained Var):** Used to describe the proportion of variance that can be explained

$$R^2 = 1 - \frac{\text{MSE}}{\text{Var}(y)}$$

Lies between 0 < R^2 < 1. Having a **higher explained variance** implies a **stronger relationship** between the points and the line, as MSE measures the difference between our **predicted and actual value** while variance measures the difference between the **average and actual value**. Hence a better model ought to have a lower MSE which in turn leads to a higher Explained Variance.

## Bias – Variance

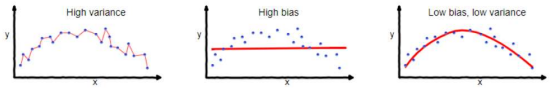
**Overfitting**

Generally, when the train set accuracy has an overly high R-Square, this implies **overfitting**. Our model has a **low bias but high variance** as it begins to curve too much (Linear Regression can include values of powers higher than 1).

Another way we can cause overfitting is by including too many features.

**Underfitting**

When we use too few features or a small train set, our model begins to have **a high bias but low variance.** This is also known as **underfitting.** The model is fails to capture and generalise the relationship of the data and performs poorly on both the train/test set.




## Classification

- Problem: Sometimes the dataset we are provided has imbalanced classes. Hence to do so we should consider down sampling or up sampling.

## Decision Tree

- Tries to form partitions in the dataset based on **max depth** chosen
- At each node, the dataset is partitioned based on a certain numeric value
- Features that appear higher in the tree are implies to have greater feature importance as well
- The **response/class** is then decided based on the highest probability of the node you belong to

**Measure of accuracy of model**

**Gini Index (Metric of Misclassification):** Tries to find the probability of wrongly classifying

$$\text{Gini}(p_1, p_2, \ldots, p_k) = \sum_{i=1}^{k} p_i(1 - p_i) = 1 - \sum_{i=1}^{k} p_i^2$$

Minimising the Gini Index implies a more accurate prediction is made.

**Accuracy (Confusion Matrix)**

A confusion matrix is used to express the **True Negatives, True Positives, False Negatives, False Positives** of our predicted results. TPR (Sensitivity), TNR (Specificity)

*After the Model is Trained/Fit on Train Data*

| Actuals \ Predicted | N | P |
|---|---|---|
| N | TN | FP |
| P | FN | TP |

**Classification Accuracy** $acc = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$

True Negative Rate $tnr = \frac{\text{TN}}{\text{TN} + \text{FP}}$ False Positive Rate $fpr = \frac{\text{FP}}{\text{FP} + \text{TN}}$

False Negative Rate $fnr = \frac{\text{FN}}{\text{FN} + \text{TP}}$ True Positive Rate $tpr = \frac{\text{TP}}{\text{TP} + \text{FN}}$

Additionally, we should also take into account the **precision and recall**,

$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

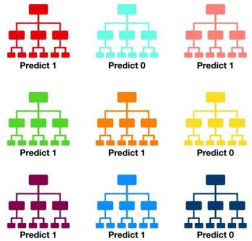
**F1 Score** should be used to create a **harmonic mean** as it takes both the **accuracy of precision and recall**. In reality, a large amount of our data is affected by True Negatives (TN). However, what we want to consider are the False Negatives (FN) and False Positives (FP).

**Note:** Having a high number of True Positives and True Negative is good, but we need to consider our False Negatives (e.g., Identifying Covid Patients as Non-Covid) as it can have serious implications

## Random Forest

- Ensemble learning method that builds multiple decision trees
- Each tree uses **some randomly chosen** features and is trained on **randomly chosen** data points
- Trees are trained **parallel** to one another with no interdependence
- Final results are then collated to obtain a good decision tree

**Why:** Having multiple trees allow the trees to learn from each other. Additionally, this helps to reduce **overfitting (low bias, high variance).** However, higher bias can occur as each model is simpler and shallower. Furthermore, the trees are trained on fewer points. (**High bias due to part of the training data and features being used**).




## Cross Validation

Split the dataset into **k partitions** of which 1 partition is used as the test set. It is a useful technique for assessing the effectiveness of your model, particularly in cases where you need to **mitigate overfitting.** This is because your model gets trained on differently on all parts of the dataset.

Example: K-Folds, Leave one out (High Variance due to high intersection of dataset)

## Clustering

## K-Means

- Choose K Clusters
- K-Means randomly chooses the K-Clusters (K-Means++ chooses the furthest points with equal probability to the centroid)
- For each point in the dataset, assign it to the nearest centroid
- For each cluster, compute the Within Sum of Squares (WSS)
- Recompute the new centroid (Iterate the process again until the centroids do not update)

**Within Cluster Sum of Squares (WSS)**

$$WSS = \sum (dist.frm.centroid)^2$$
$$= \sum\left[(x_i - \bar{x})^2 + (y_i - \bar{y})^2\right] = n\sigma^2(x) + n\sigma^2(y)$$

There are two kinds of WSS to consider, **Total WSS** and **Average WSS**. Average WSS divides the WSS by the number of points in the cluster.

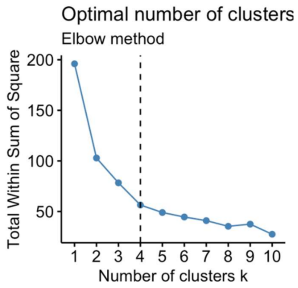
**Choosing the optimal clusters:**

**Elbow Method**: Plot the Total WSS against K-Clusters. Try to identify the point where increasing the number of clusters does not influence the Total WSS much. We will denote this K0 as the optimal number of clusters.

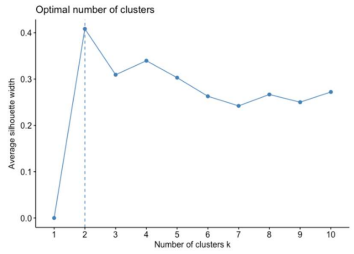
K < K0: Increasing K will change the Total WSS significantly

K > K0: Increasing K will not have much change on the Total WSS

K = K0: The point where WSS has decreased sufficiently and is at its saturation point




**Average Silhouette Method:** Measures the quality of a clustering. It determines how well each object lies within its cluster. A high average silhouette width indicates a good clustering.




**Drawbacks of K-Means**

- K-Means is highly dependent on the choice of initial clusters (Improved via K-Means++)
- Favours spherical shaped clusters due to the nature of computing centroid via Euclidean Distance

**Proposed Alternatives**

- DBSCAN: Density Based clustering that tries to include a point in the cluster if it is within the distance/epsilon(eps) value chosen. DBSCAN is great at **separating high density clusters from low density clusters**, however, it **struggles with clusters of similar density**.
- Hierarchical Clustering/Dendrogram: Used to join the points closer to one another in a **bottom-up approach**. Helps you to analyse how the dataset would be partitioned further and further. (Its like a cluster within a cluster)
- Expectation Maximization Algorithm (Gaussian): A form of **soft clustering** that tries to use a normal distribution to identify the clusters. Points are not fixed to one cluster but rather given a probability of being in a cluster. The mean and covariance are used to iteratively recompute the centroid. It assumes that for each data point, there is a hidden latent variable.

## Anomaly Detection

## Local Outlier Factor

- Choose k, number of neighbours and d, fraction of anomalies
- For each point, compute the K-nearest neighbours
- Find the reachability distance to the Kth point
- Compute the Local Reachability Distance for each point (Lower implies anomaly)
- Calculate the LOF (LOF > 1 imply an outlier, LOF < 1 imply an inlier)

**Drawbacks of LOF**

- LOF goes by density and hence sparse areas of points are automatically considered as clusters
- Outliers may not appear in 1-d axis
- It is not easy to decide which specific threshold determines if a point is an outlier. Only LOF < 1 is clear implication of inlier

**Proposed Alternatives**

Isolation Forest: Using decision trees to continually partition the dataset until an anomaly is found

## Recommenders

User-Item Matrix (Each row / column can be treated as a vector)

**Types of similarity:** Item-Similarity, User-Similarity, Global Trends

Recommenders can be done through 2 ways, content filtering (Using similar features of items) and collaborative filtering (Using preference and tastes to find similarities).

**Euclidean Distance:**

- Useful for computations where magnitude matters (Movie ratings)
- Place large emphasis on distance

**Jaccard Similarity:**

- Useful for computations of binary variables (Either bought or never bought the product)
- Does not place any emphasis on magnitude

**Cosine Similarity:**

- Useful for computation of similarity where magnitude is not important (Person 1 watches the exact same movie as Person 2 but twice as much. However, they are treated to have the exact same taste)
- Place large emphasis on the angle

## Must Know!

**Mean**: Represents the average (affected by outliers)

**Median:** The middle number after ordering the points (ignores outliers)

**Quartiles:** Measures the spread of values above and below the means by dividing the data into three points – lower quartile (Bottom 25%) – Median – upper quartile (Upper 25%).

**Standard deviation**: Looks at how spread out the data is from the mean

**Variance:** Average degree to which each point differs from the mean

**Skewness:** Measure of symmetry of the probability distribution of data

**Pearson Correlation**: Used to measure the relationship between 2 continuous variables (-1 to 1)

**Boxplot:** Median, Inter-quartile range, Upper quartile, Lower quartile, Whiskers, Outliers. Boxplot is useful as it gives a statistical summary of the data (Quartile ranges, Outliers etc). 5-point statistic that breaks open the data in equal proportion (25%)

**Histogram:** Provides a visual representation of the distribution of data. Can be used to show the skewness of data as well. (Used with **KDE Plot:** Provides a smoother estimate of the data, has greater flexibility)

**Jointplot:** Helps us to better visualize the correlation between 2 numeric variables

**Heatmap:** It can express correlation (-1 to 1) and gives colours to extreme value which make it visually easier to interpret

**Structured Data:** Organized, Easy to Read, Quantitative (Numeric, Classes)

**Unstructured Data**: Unorganized, Qualitative (Audio, Visual, Texts)

**Supervised Learning (Regression, Classification):**

The dataset is labelled. Outputs and inputs are known to the user. Hence, the model can measure its accuracy and try to adjust in order to iteratively improve

**Unsupervised Learning (Clustering, Anomaly Detection):**

Output is not known. Input data is not known. Generally, less accurate.